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Predictive Control of Thermal Storage Systems Designed for Multi-energy District Boilers: A Case Study in France

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Abstract

The present work deals with improving the operation of a multi-energy district boiler by adding to the plant an optimally-designed thermal storage tank and developing a model-based predictive controller in order to manage it. The proposed architecture generates optimal command sequences dealing with the amount of thermal energy to be stored or released. In order to implement such a controller, one needs to forecast the power demand. As a consequence, a short-term forecast method, based on both a Multi-Resolution Analysis (MRA) and feedforward (multilayer) Artificial Neural Networks (ANN) is proposed. The present paper mainly focuses on the impact of Thermal Energy Storage (TES) on the functioning of a northeast France multi-energy district boiler selected as a case study. As a result, both the fossil energy consumption and CO_2 emissions are significantly reduced while the economic gain is increased.

Keywords: *multi-energy district boiler, thermal energy storage, model predictive control, artificial neural networks, power demand.*

1. Introduction

Because of the global energy crisis, the French government supports the renewable energy production. As buildings account for about 40% of total final energy consumption (more than half of this consumption is due to heating), France makes a specific effort in this sector. In addition, using biomass materials such as wood in industrial and residential heating can significantly reduce the reliance on fossil fuels and limit the CO_2 emissions (Kitzing et al., 2012). In 2000, Tanaka et al. showed that a seasonal storage system is able to decrease the consumption of energy by about 26% in a District Heating and Cooling (DHC) plant (Tanaka et al., 2000). As another interesting work, Smith et al. highlighted the benefits of storing thermal energy, in combination with CHP (Combined Heat and Power) technology (Smith et al., 2013). In 2011, Verda and Colella evaluated the effects of thermal energy storage on both the primary energy consumption and cash flows in district heating networks (Verda and Colella, 2011). Gustafsson and Karlsson showed how a thermal storage system can be used in a CHP plant for decreasing both the demand in district heating and the consumption of electricity (Gustafsson and Karlsson, 1992). In 2010, Kavvadias et al. proposed a parametric analysis as an efficient way to design CHP plants optimally (Kavvadias et al., 2010).

As a key point, advanced control techniques and management strategies are needed to improve the operation of multi-energy district boilers managed by Cofely GDF-Suez, our industrial partner. In this sense, the OptiEnR research project focuses on optimizing performance by adding thermal storage systems to the plants. First, we assessed a specific case study (Eynard et al., 2012) and we are now developing a flexible and generalized approach. It has been highlighted in a previous work that once optimally designed and managed using a sequential approach based on logical conditions, a thermal storage tank can significantly improve the overall efficiency of a plant, in particular in case of badly-sized heat generators (Labidi et al., 2014). So, the present paper deals with the optimal management of a thermal storage tank using a Model Predictive Controller (MPC). We focused on analyzing the energy savings one can achieve using such an

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advanced control approach. The power demand is forecasted using the MRA-ANN methodology. Its particularity comes from the combination of signal processing (a wavelet-based multi-resolution analysis) and artificial intelligence (multilayer artificial neural networks) tools. Lastly, a case study is selected in order to evaluate the predictive control approach.

The next section of the paper (section 2) provides a brief description of multi-energy district boiler operation. Then, the performance indicators are presented (section 3). In section 4, the design of the MPC controller allowing the thermal storage tank to be efficiently managed is carried out. Next, the developed MRA-ANN methodology is presented (section 5). Such an approach has proven to be effective in forecasting time series. It should also be noted that several other methods for power demand forecasting have been suggested and implemented (Amjady and Keynia, 2009; Dotzauer, 2002). The particularity of the proposed methodology comes from the combination of signal processing and artificial intelligence tools. Lastly, a case study is selected in order to both validate the MRA-ANN forecasting methodology and evaluate the predictive control approach (section 6). In particular, it is highlighted that the way the tank is designed and managed is a key factor in plant operation improvement. The paper ends with a conclusion and an outlook to future work.

2. Multi-energy district boiler operation

Typically, in multi-energy district boilers, the biomass units (characterized by a minimum (P_{WB}^{min}) and a maximum (P_{WB}^{max}) heat production capacity are generally sized in order to meet the major part of the power demand but they lack the capability of covering the peak loads. So, auxiliary fossil boilers are used during the coldest periods of the year, in case of shutdown maintenance activities or when the power demand is lower than P_{WB}^{min}. As stated in section 1, the main purpose of the present study is to optimize the operation of multi-energy district boilers by adding to the plants optimally-managed thermal storage tanks. Because the sequential approach we proposed initially does not take into account future power demand values, such an approach seems to be sometimes unable to optimize the whole system, in particular in case of high variability in the power demand. For this reason, we propose here an advanced strategy based on both a Model Predictive Controller (MPC) and a forecasting approach.

3. Performance indicators

In order to assess the impact of both the thermal storage system and the management strategy, energy, economic and environmental criteria are suggested as performance indicators. Because the main purpose of thermal energy storage is to decrease the consumption of gas, the gas coverage rate (C_{gas}) is proposed as an energy indicator (eq. 1). It is calculated from the thermal energy produced by the combustion of gas (E_{gas}) and wood (E_{wood}) during the considered period:

$$C_{gas} = \frac{E_{gas}}{E_{gas} + E_{wood}} \qquad \text{(eq. 1)}$$

The wood coverage rate (C_{wood}) is computed in the same way than C_{gas} and is subject to contract (eq. 2):

$$C_{wood} = \frac{E_{wood}}{E_{gas} + E_{wood}} \qquad \text{(eq. 2)}$$

With the aim of highlighting the economic benefits of energy savings, a criterion (Ec) is defined from E_{gas}, E_{wood}, UP_{gas} (the unitary price of gas), and UP_{wood} (the unitary price of wood) (eq. 3):

$$Ec = E_{gas} \times UP_{gas} + E_{wood} \times UP_{wood} \qquad \text{(eq. 3)}$$

In order to put in perspective these economic benefits, the economic gain G is evaluated (eq. 4). It is defined as the difference between $Ec(V)$, the economic cost related to energy consumption, considering a storage volume V, and $Ec(V = 0)$, the economic cost related to energy consumption without storage of thermal energy ($V = 0$ m^3):

$$G(V) = Ec(V) - Ec(V = 0) \qquad \text{(eq. 4)}$$

The environmental impact of such a technology is evaluated thanks to criterion L_{CO2}, which is about CO_2 emissions (eq. 5). L_{CO2} is expressed from Ec_{gas}, Ec_{wood} and the Life-Cycle Assessment of CO_2 emissions from gas (U_{CO2}^{gas}) and wood (U_{CO2}^{wood}):

$$L_{CO2} = Ec_{gas} \times U_{CO2}^{gas} + Ec_{wood} \times U_{CO2}^{wood} \qquad \text{(eq. 5)}$$

It should also be noted that new buildings connected to the heat network as well as future expansions of existing buildings are factors to be taken into account in order to evaluate the proposed strategy accurately. As a result, one can consider an increase in the power demand P_{net} up to 30 % and evaluate the impact of such an increase on plant operation.

4. Design of the Model-based Predictive Controller (MPC)

4.1. Principles of MPC

It is somewhat curious to note that the concept of Model-based Predictive Controller (MPC) has a long history that began during the 1970's when Engineers at Shell Oil developed their own dependent technology with an initial application in 1973 (Garcia et al., 1989). Nowadays, this concept is widely used in the control of industrial processes. Its popularity in industry is mainly due to the possibility it offers to treat operating specifications and constraints jointly during the development phase of the controller. For instance, MPC is commonly used to manage thermal comfort (Castilla et al., 2014) and energy resources (Ma et al., 2012) in buildings.

The philosophy of MPC is down to use a model to forecast the behavior of the system to be controlled and choose the best decision in the sense of an objective function while satisfying constraints. Usually, the aim is to ensure the desired set-point, regardless of disturbances with minimal effort. Constraints deal with physical limitations and are introduced for economic or security reasons. The forecast horizon is the time interval during which the objective function is minimized using an optimization algorithm (Manenti, 2011).

4.2. Structure of the controller

In this subsection of the paper, the proposed model-based predictive controller is presented. It uses a model of the multi-energy district boiler (section 4.2.1) as well as a forecast unit allowing the power demand (P_{net}) to be accurately estimated over the next 24 hours (section 4.2.2). This unit makes use of both a wavelet-based Multi-Resolution Analysis (MRA) and feedforward (multilayer) Artificial Neural Networks (ANN). The optimization problem is solved using the fmincon (*find minimum of constrained nonlinear multivariable function*) algorithm of Matlab® (sections 4.2.3 and 4.2.4). The controller's structure is depicted by Fig. 1:

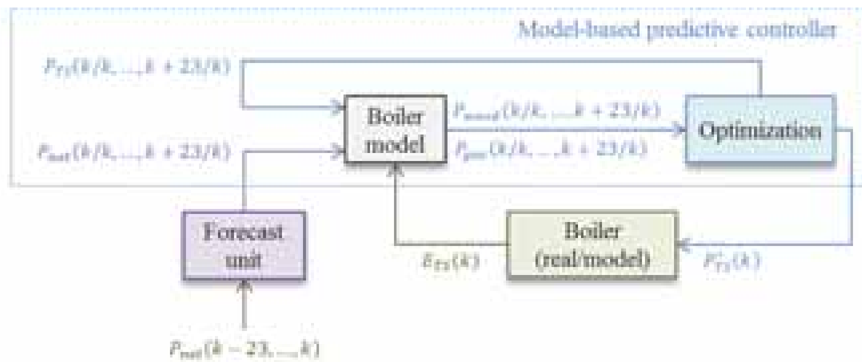

Fig. 1: Structure of the proposed controller (P_{net} is the power demand, P_{TS} is the thermal charging/discharging power, E_{TS} is the amount of energy stored or released, P_{gas} is the gas power, and P_{wood} is the wood power)

4.2.1. Model of the multi-energy district boiler

The proposed predictive controller uses the model of a multi-energy district boiler equipped with a thermal storage tank we developed and described in a previous work (Labidi et al., 2013). P_{gas} (the gas power) and P_{wood} (the wood power) are defined as functions of both the charging/discharging power of the storage tank (P_{TS}) and the power demand (P_{net}). k is the time step. The model is based on the 3 following cases, with P_{WB}^{min} and P_{WB}^{min} the wood boiler(s) minimum and maximum heat production capacities, respectively (eqs. 6 to 8):

$$\text{if } P_{WB}^{min} \leq P_{net}(k) \leq P_{WB}^{max} \text{ then } P_{wood}(k) = P_{net}(k) + P_{TS}(k) \text{ and } P_{gas}(k) = 0 \quad \text{(eq. 6)}$$

$$\text{if } P_{net}(k) \geq P_{WB}^{max} \text{ then } P_{wood}(k) = \max\left(P_{WB}^{max}, P_{net}(k) - P_{TS}(k)\right) \text{ and } P_{gas}(k) = P_{net}(k) - P_{wood}(k) \quad \text{(eq. 7)}$$

$$\text{if } P_{net}(k) \leq P_{WB}^{min} \text{ then } P_{wood}(k) = \max\left(P_{WB}^{min}, P_{net}(k) + P_{TS}(k)\right) \text{ and } P_{gas}(k) = 0 \quad \text{(eq. 8)}$$

4.2.2. Concept of time series for power demand forecasting

As it is mentioned in the previous section, P_{net} (the power demand) is a district boiler model input. So, it has to be accurately forecasted. So, a methodology based on a Multi-Resolution Analysis (MRA) and feedforward (multilayer) Artificial Neural Networks (ANN) is proposed in order to forecast time series (Brockwell and Davis, 1991, 1997). The main idea behind such a methodology is to replace the forecasting of an original signal with high variability by the estimation of its wavelet coefficients (Fig. 2). These coefficients are distinguished by specific levels of frequency as well as a variability which is lower than the variability of the original signal. As a result, the forecasting process is easier. Such an advanced approach has been developed because linear approaches like AR, ARMA or ARIMA proved to be insufficiently efficient, due to a high variability in power demand.

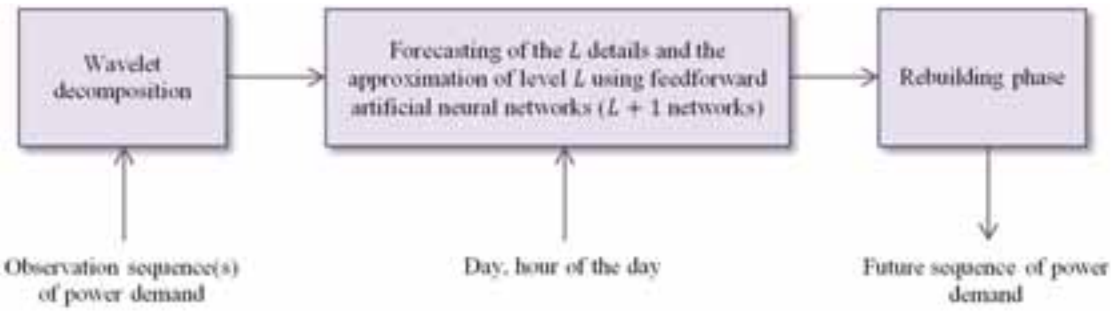

Fig. 2: MRA-ANN forecasting methodology

A time series can be defined as a sequence of numerical data points in successive order, usually occurring in uniform intervals. According to that, time series forecasting consists in using a model to estimate future values on the basis of observations. In our case, the model aims at estimating the power demand over the next 24 hours, using a set of M observation sequences whose length is also 24 hours (because of the daily cycles we observed in the data). We decided for a forecast horizon (H_f) of 24 hours as an interesting compromise between forecasting accuracy and periodicity in power demand. In addition, such horizon is well adapted to the charging and discharging cycles of the tank.

4.2.2.1. Wavelet-based multi-resolution analysis

The wavelet transform aims at decomposing a given signal into wavelets (i.e., highly localized small oscillations) (Heil and Walnut, 1989; Gubner and Chang, 1995). Unlike the Fourier transform, it offers time and frequency localization. There are two types of wavelet transforms: the Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT). We focus here on the second one. First, through Low Pass (LP) and High Pass (HP) filters, an original signal S is decomposed into low (approximations) and high (details) frequency coefficients of level 1. By decomposing successively the low frequency coefficients only, we can produce L levels of decomposition. Fig. 3 shows the decomposition of level L of a signal x. In order to rebuild that signal, we have just to sum the L details (D_1, D_2, D_3, …, D_L) and the approximation of level L (A_L) (Mallat, 1989). It should also be noted that different families of wavelets may be chosen. Because the Daubechies wavelets (Daubechies, 1992) have the highest number of vanishing moments, this family has been chosen. Finally, the impact on performance of both the decomposition level and the wavelet order has been studied.

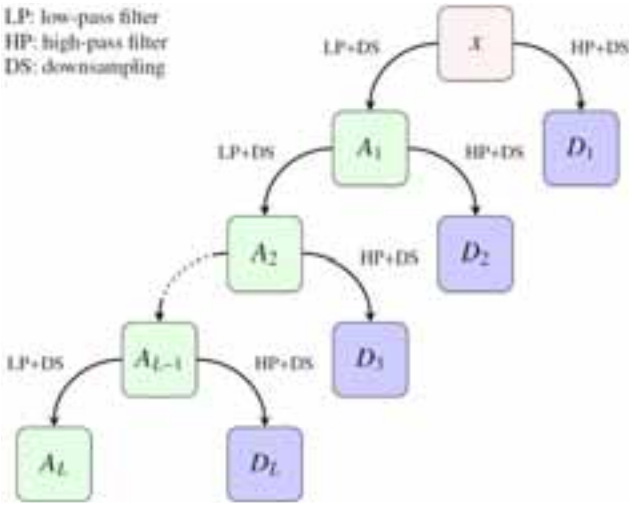

Fig. 3: Wavelet-based multi-resolution analysis leading to the decomposition of level L of a signal x

4.2.2.2. Feedforward artificial neural networks

Multilayer artificial neural networks can be used to forecast time series (Hornik et al., 1989; Kourentzes et al., 2014). Usually, each network consists in one layer of linear output neurons and one or more hidden layers of nonlinear neurons. As it is well known, the research for the adequate topology of a neural network (i.e., its number of hidden layers and neurons) is a key point. Such a research is based on a training (learning) phase during which the generalization capability of the network is controlled and its parameters are identified (Charalambous, 1992, Hagan and Menhaj, 1994).

4.2.2.3. Optimal configuration

Tab. 1: Optimal configuration and evaluation of performance

Parameter	Value
Wavelet family	Daubechies
Wavelet order	4
Decomposition level	1
Number of observation sequences	1
Number of hidden neurons	17
FIT	72.26%
MAE (Mean Absolute Error)	299.57 kW
MRE (Mean Relative Error)	5.9%

First, the time series (i.e., historical data covering a period of six months, from September 21 to April 16) is split into sequences of 24 hours, with a sampling time of 1 hour. Then, the wavelet-based multi-resolution analysis allows these sequences to be decomposed into subsequences (i.e., approximation and details coefficients). Using this database, multilayer artificial neural networks can be trained. As a key point, one network is used in order to forecast each subsequence. So, $L + 1$ networks are needed to forecast L detail coefficients and the approximation coefficient of level L. The hour of the day and the day of the year are complementary model inputs. Once all the subsequences are forecasted, they are summed to obtain the values of power demand over the next 24 hours. In order to improve forecast accuracy, we optimized the topology of the networks (note that we considered single-hidden layer structures and searched for a common topology for all the networks so as to simplify the optimization process), the decomposition level (L) and the number of observation sequences (M). Table 1 deals with the optimal configuration and performance. Results highlight the ability of such an approach to achieve the task of prediction with accuracy.

4.2.3. Optimization problem

At each time step, the controller defines the optimal values of the charging/discharging power (P_{TS}), along the forecast horizon H_f (i.e., over the next 24 hours). Note that a positive value ($P_{TS} > 0$) stands for the charging (storage) mode whereas a negative value ($P_{TS} < 0$) is for the discharging (release) mode. So, the main goal of the control approach is to minimize the use of fossil energy by optimizing the storage process during low-demand periods and releasing the thermal energy stored when the power demand is high. Thus, the objective function J is defined as the quadratic sum of the gas power consumed at each time step, along the forecast horizon (i.e., over the next 24 hours). The optimization problem comes down to find, at each time step, the charging/discharging power (P_{TS}) such that J is minimized (eq. 9) and the constraints are met (eqs. 10 and 11):

$$\min_{[P_{TS}(k/k),\dots,P_{TS}(k+H_f-1/k)]}\left(J=\sum_{k=1}^{H_f} P_{gas}(k)^2\right) \quad \text{(eq. 9)}$$

Two constraints ensure that thermal energy is stored or released adequately. The first one (eq. 10) is introduced in order to limit the interval of the possible values for P_{TS}. This constraint is related to the characteristics of the storage tank feed pumps. The second constraint (eq. 11) makes reference to the design of the storage system. In other words, it is related to the capacity of the tank ($E_{max} = \rho \cdot C_p \cdot V \cdot \Delta T$, with ρ the water density, C_p the specific heat of water, V the volume of the storage system and ΔT the difference in temperature between hot and cold water). E_{init} is the amount of thermal energy initially stored in the tank. So, at each time step, the amount of energy stored has to be positive and lower than E_{max}:

$$-P_{TS}^{max} \le P_{TS}(k+j/k) \le P_{TS}^{max}, \forall j \in [\![0; H_f-1]\!] \quad \text{(eq. 10)}$$

$$0 \le E_{init} + \textstyle\sum_{i=0}^{j} P_{TS}(k+i/k) \le E_{max}, \forall j \in [\![0; H_f-1]\!] \quad \text{(eq. 11)}$$

4.2.4. MPC algorithm

Fig. 4 depicts the MPC algorithm used. At each time step k, a simulation over the forecast horizon based on the non-predictive (sequential) strategy (Labidi et al., 2014), the current amount of energy stored in the tank, and the forecasted values of P_{net} is performed in order for the values of $[P_{TS}(k/k),\dots,P_{TS}(k+H_f-1/k)]$ to be initialized. These values are then optimized using both the non-linear optimization algorithm "fmincon" from Matlab® and the developed model of the multi-energy district-boiler. The first optimized value is applied to the model which stands for the real system and so on until the end of the simulation process. Then, the performance indicators are computed for an off-line analysis of the results.

4.2.5. Non-predictive strategy

This strategy is based on the three following operation modes (Labidi et al., 2014):

- **Operation mode 1**: When the power demand is high (in particular during the coldest months of winter), instead of modulating the biomass power, all the (biomass) units available operate at maximum power to meet requirements and charge the tank. Once the power demand is upper than P_{WB}^{max}, the stored energy is released. In this way, the auxiliary gas unit is only switched on when the tank is empty and the power demand still exceeds P_{WB}^{max}.
- **Operation mode 2**: This second operation mode is for a moderate power demand. When $P_{net} < P_{WB}^{max}$, due to the variability in the demand, the biomass boiler (or one of the two biomass units installed at the plant) operates at minimum power (or higher) and the excees of energy produced is stored in order to be used later. If two biomass boilers are available, both can also operate at minimum power. In this way,

these units operate continuously and the number of on/off transitions is reduced. As a consequence, fossil energy can be saved.

- **Operation mode 3**: For some periods of the year (in particular during the hottest months of summer), most of the buildings connected to a heat network do not need to be heated and, as a consequence, only domestic hot water is required (low-demand periods). Instead of using the auxiliary gas unit to meet low power requirements (biomass boilers are usually oversized), the biomass unit (or the smallest boiler in case of two units being installed at the plant) and the thermal storage system can be operated as follows: first, the biomass unit runs at minimum power, what allows both the power demand to be met and the tank to be charged. Once the thermal storage system is completely filled with hot water, the boiler is shut down and the stored energy is released to afford domestic hot water. The boiler is switched on again when the tank is empty. Such a mode prevents the use of gas and favors the use of renewable energy during low-demand periods.

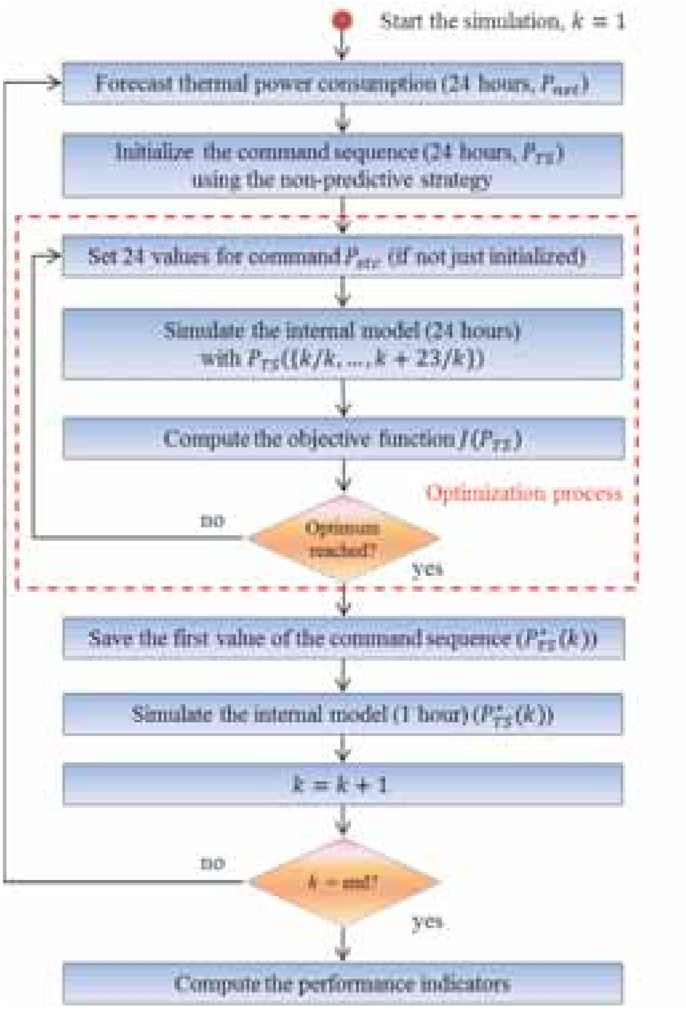

Fig. 4: MPC algorithm

5. Simulation results

5.1. Case study

We selected as a case study a multi-energy district boiler managed by Cofely GDF-Suez and located in the northeast of France, in the Alsace region (Haut-Rhin). Alsace has a semi-continental climate with cold and dry winters and hot summers. Winter starts in December and ends in February and has an average temperature of around 2 degrees Celsius across the season. January is the coldest month of the year with the lowest average temperature of 1 degree Celsius. Winter is also the time of year with the lowest levels of precipitation. Summer starts in June and ends in August. It sees the highest levels of rainfall of the year as well as the highest temperatures with an average temperature of 18 degrees Celsius across the season. The plant is composed of three heat generators (Fig. 5).

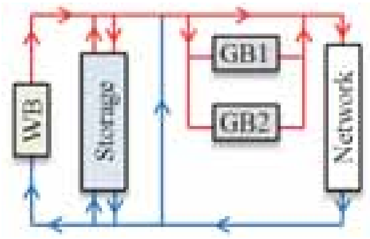

Fig. 5: Synoptic of the multi-energy district boiler

The first generator (WB) is a biomass boiler whose minimum power (P_{WB}^{min}) is 1050 kW. Its maximum power (P_{WB}^{max}) is 4200 kW. This unit is designed to ensure the basic production. A 7000 kW gas boiler (GB1) operates jointly with it during peak demand periods or alone when the power demand is lower than P_{WB}^{min}. A 9000 kW gas boiler (GB2) is switched on in case of malfunction or during maintenance phases only. Table 2 summarizes the characteristics of the boiler units.

Tab. 2: Characteristics of the boiler units

Boiler unit	Power (kW)	Efficiency (-)
WB	1050	0.70
	2100	0.75
	3150	0.88
	4200	0.95
GB1	140	0.97
	7000	0.97
GB2	180	0.97
	9000	0.97

5.2. Control results

Tab. 3: Simulation parameters

Parameter	Value
Simulation period	From September 1 to April 16
Sampling time	1 hour
Forecast horizon (H_f)	24 hours
UP_{gas}	40 € MWh^{-1}
UP_{wood}	17 € MWh^{-1}
U_{CO2}^{gas}	234 kgCO_2 MWh^{-1}
U_{CO2}^{wood}	13 kgCO_2 MWh^{-1}

Table 3 summarizes the main simulation parameters. Concerning the impact of the proposed strategy, simulation results show that the biomass boiler is sized to ensure around 85% of the power demand during the simulation period without thermal storage tank. Fig. 6 depicts the way both the gas coverage rate and the CO_2 emissions evolve according to the volume of the tank. One can clearly note that the MPC strategy allows a significant decrease in gas consumption and consequently in CO_2 emissions. Fig. 7 depicts the way the size of the tank impacts on Ec and G, respectively. One can highlight that Ec decreases with the size of the tank. Furthermore, using the proposed MPC strategy, a considerable economic gain is realized. Regarding the ability of the thermal storage tank to cope with a possible increase in power demand, one can observe (Fig. 8) that the proposed strategy allows the wood coverage rate to be 4 to 10 points higher than when the reference scenario (RS) is considered (i.e., no thermal energy storage). In addition, on the basis of the parametric study, one can define the optimal size of the tank. For this case study, 300 m^3 can be chosen.

6. Conclusion

The present paper deals with optimizing the performance of a multi-energy district boiler. The plant is connected to a heat network for thermal energy distribution. First, a model predictive controller has been developed in order to optimize the use of the thermal storage tank. In order to implement this controller, the power demand has to be accurately forecasted. As a result, a methodology based on a Multi-Resolution Analysis (MRA) and multilayer Artificial Neural Networks (ANN) is proposed. One can highlight that the proposed control scheme allows the fossil energy consumption to be significantly reduced. The same remark applies to the functioning costs and CO_2 emissions. Future work will focus on improving the forecasted model, using self-growing artificial neural networks trained with the cascade correlation algorithm, and considering other objective functions. Finally, the proposed approach will be implemented *in situ*.

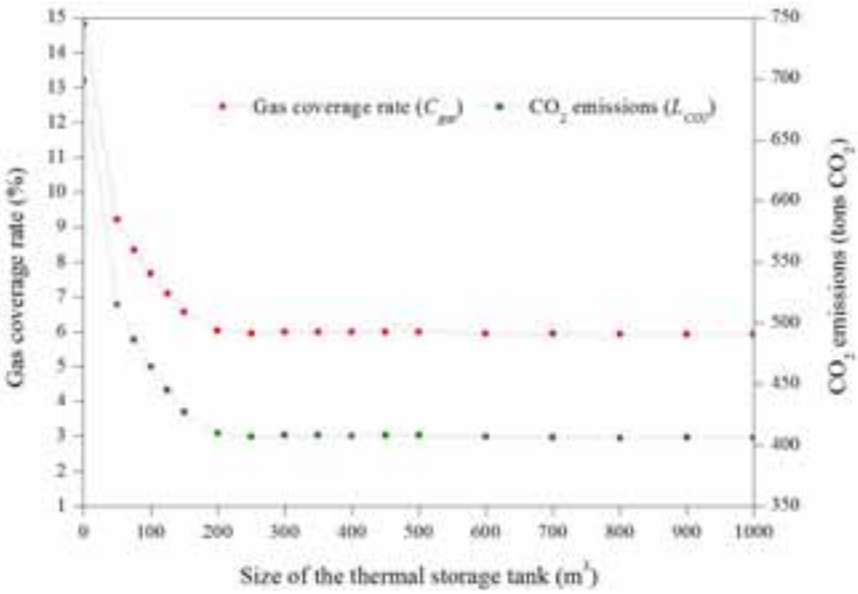

Fig. 6: Impact of the size of the thermal storage tank on the gas coverage rate (C_{gas}) and CO_2 emissions (L_{CO2})

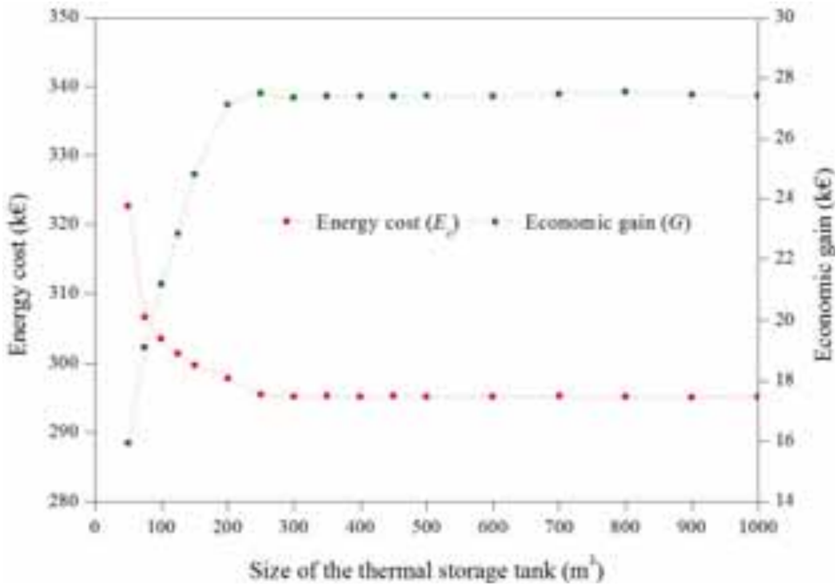

Fig. 7: Impact of the size of the thermal storage tank on the energy cost (Ec) and economic gain (G)

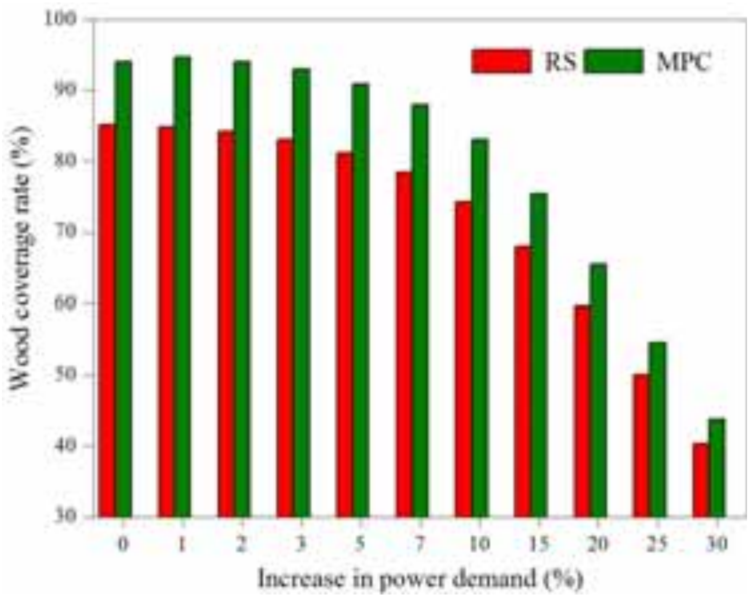

Fig. 8: Impact of an increase in power demand on the wood coverage rate (C_{wood}) (see section 3), with (MPC strategy) or without (Reference Scenario) thermal energy storage

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